

Review

Vehicle-to-Vehicle Energy Trading Framework: A Systematic Literature Review

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Abstract: As transportation evolves with greater adoption of electric vehicles (EVs), vehicle-to-vehicle (V2V) energy trading stands out as an important innovation for managing energy resources more effectively as it reduces dependency on traditional energy infrastructures and, hence, alleviates the pressure on the power grid during peak demand times. Thus, this paper conducts a systematic review of the V2V energy trading frameworks. Through the included article analysis ($n = 61$), this paper discusses the state-of-the-art energy trading frameworks' structure, employed methodologies, encountered challenges, and potential directions for future research. To the best of the authors' knowledge, this is the first review explicitly focused on V2V energy trading. We detail four critical challenges to face while establishing the framework in current research, providing an overview of various methodologies, including auctions, blockchain, game theory, optimisation, and demand forecasting, that are used to address these challenges and explore their integration within the research landscape. Additionally, this paper forecasts the evolution of V2V energy trading, highlighting the potential incorporation of advanced and established technologies like artificial intelligence (AI), digital twins, and smart contracts. This review aims to encapsulate the existing state of V2V energy trading research and stimulate future advancements and technological integration within the field.

Keywords: vehicle-to-vehicle; energy trading; distributed energy resource; electric vehicle



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1. Introduction

The electrification of transport is essential for the reduction in GHG emissions, as noted by IEA net zero scenarios (2021) [1]. A mix of factors is contributing to the adoption of electric vehicles (EVs), including supportive government policies [2], increasing consumer awareness of environmental issues, diverse sources for electricity, such as waste heat recovery using thermoelectric [3], volatility in price, and insecure access to fossil fuels [4]. In the UK, a country that has a legally binding target of reducing its emissions to net zero by 2050, the role of EVs in decarbonising transport emissions has been recognised. With the EV infrastructure strategy [5], the sale of new petrol and diesel vehicles and vans in the UK will cease by 2030, and all new cars and vans will be fully zero-emission at the tailpipes by 2035. The number of EVs is experiencing extremely rapid growth. In 2023, the new registered EVs reached 315,000 [6], and in total, 975,000 fully electric cars were on the road by the end of December 2023 [7]. However, the widespread integration of EVs into the energy grid introduces new challenges. Uncoordinated and random charging activities by EVs can increase the burden for distributed systems and may cause network voltage fluctuation [8,9]. The demand for charging a large number of EVs can place a significant burden on the grid at peak times, especially between 8 a.m. and 10 p.m. [9,10]. This burden, if not addressed properly, may lead to increased incidents of power grid overloading or even blackouts. Meanwhile, power losses during charging and transformer and feeder overload are other problems that need to be addressed [11].

The evolution of distributed energy resources (DERs) has significantly transformed the energy distribution landscape [12]. EVs, as an integral component of DER, could be

transitioned from mere energy consumers to potential energy producers [13]. This shift opens up various options for managing surplus energy in EVs:

1. EV owners can retain excess energy for later consumption [14,15]. However, for EV owners whose households are equipped with solar panels, the amount of energy that could be retained is limited by the storage capacity of the EVs [16] and household batteries. Once the battery capacity is reached, any additional energy generated is not utilised, leading to potential wastage;
2. EVs can supply surplus energy back to the grid at predetermined prices [17–19]. While this enables the sale of excess electricity, the compensation offered by the grid is relatively low [20], making it a less attractive option for EV owners;
3. EVs with excess energy could directly sell energy to other EVs in need. This energy transaction directly among EVs is also identified as vehicle-to-vehicle (V2V) energy trading [21]. Compared to other more well-known EV-based energy-sharing solutions like vehicle-to-grid (V2G) and vehicle-to-house (V2H) energy trading, V2V energy trading can bring much more social and economic benefits to the participants. Social benefits emerge from the flexibility of trading power when and where it suits the consumer. While V2G technology allows EVs to return electricity to the power grid, aiding in managing grid loads and supporting grid stability [22], and V2H technology enables EVs to supply power directly to a home, potentially serving as a backup power source during outages [23], these technologies primarily interact with stationary energy systems (the grid or homes). However, V2V stands out by enabling dynamic, mobile, and flexible energy interactions among EVs. From the economic point of view, the V2V energy trading can bring more economic benefits to the participants. Although the V2H framework enables the EV to feed the house with surplus energy, it provides indirect economic benefits by utilising the surplus energy to its full potential [23]. As for bringing direct economic benefits, in conventional V2G energy trading, the energy could only be transacted within a pre-determined fixed price, with an average of 15 p per kWh of buying and 5 p per kWh of selling [24]. This discrepancy between relatively high buying prices and low selling prices in the market leaves little room for EV owners to realise economic benefits from their transactions. However, in V2V energy trading, energy buyers and sellers could go through a series of negotiations and transactions. Suppose that the participants are aware of the trading price with the power grid, as mentioned before, and a fair price between 15 p per kWh and 5 p per kWh could be established, providing energy seller with a higher income and energy buyer with a lower cost compared to V2G transaction.

In this context, V2V energy trading emerges as a novel innovation that enables decentralised energy transactions among EVs. Direct energy trading among EVs is the most important feature of V2V energy trading [25,26], where EV owners could acquire demanded energy from other EVs with excess energy or potentially sell back their surplus energy to other EVs [27]. As an applied technology of decentralised energy transaction framework, V2V energy trading allows for the demand for EV charging during peak times to be partially met by other EVs, effectively reducing the pressure on the grid [28]. Furthermore, the decentralised nature of V2V energy trading is particularly beneficial for the local energy market, as it helps to decrease energy transmission losses [14,29]. This framework also offers economic advantages to both sellers and buyers [25,27,30], promising potential income for those selling excess energy and lower energy costs for purchasers.

The field of V2V energy trading has garnered considerable interest, leading to numerous projects and research efforts. However, the literature still lacks comprehensive reviews focused exclusively on V2V energy trading. This review aims to fill this gap by concentrating on V2V energy trading, clarifying the framework of V2V energy trading, assessing the current state of research, identifying challenges to face while establishing the framework, providing an overview of various methodologies, including auctions, blockchain, game theory, optimisation, and demand forecasting that is used to address

these challenges, exploring their integration within the research landscape, and providing guidance for future studies. In this paper, we present a systematic review by defining smaller and specific research questions and scoping this review systematically at each stage. This review underscores the essential need to evaluate and consolidate the existing body of research on V2V energy trading frameworks.

This paper establishes the state-of-the-art of V2V energy trading frameworks. This encompasses defining V2V energy trading, detailing its structure, and discussing the main factors that underpin its functionality (Section 3). This is achieved through the introduction of a four-module energy trading structure, which provides a comprehensive framework for understanding the complexities of V2V energy trading. Then, this review narrows its focus to the V2V module specifically. It identifies several critical challenges that need addressing within this module and reviews the related approaches proposed in recent works, which tackle the problems identified in the V2V module (Section 4). Thereafter, this review evaluates the framework's gaps in the knowledge based on different approaches (Section 4.1). Furthermore, we reflect on the potential alternative frameworks and methodologies that cover the current limitations and possible research directions in the future (Section 4.2) in this discussion. Finally, we conclude this paper (Section 5).

2. Review Methods

This review adopts a systematic review approach due to its comprehensiveness, transparency, and replicability [31], allowing for an objective assessment of the existing literature. By following a predefined and structured protocol [32], this review minimises bias (i.e., selection bias, citation bias, reviewer bias, etc.) and increases the reliability of our findings [33]. Figure 1 shows the process of the systematic review for this research.

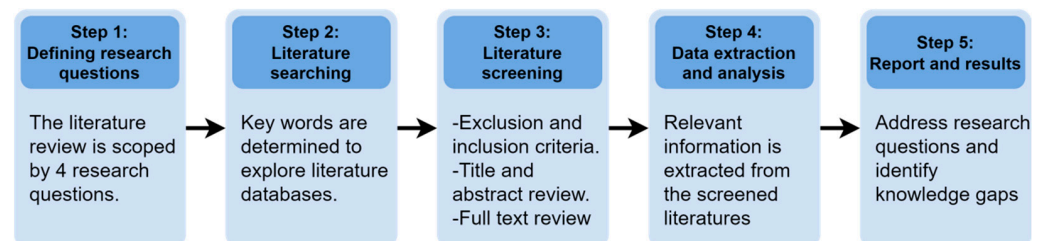


Figure 1. Process of carrying out a systematic literature review [15].

Initially, specific research questions are formulated, and relevant keywords are selected to scope this review. Then, these keywords are used to create queries and retrieve articles across several databases, including Web of Science, ScienceDirect, and Google Scholar, to gather the relevant literature. The resulting list of materials is subsequently screened through exclusion and inclusion criteria, a title, and abstract review, and then progressing to full-text assessments. Relevant methodology, contribution, and results from the selected literature are extracted and analysed for insights, as well as for their limitations. Finally, this review attempts to address the initial research questions and identify knowledge gaps and future research avenues, thus contributing to the field's body of knowledge.

2.1. The Literature Review Questions

This review is guided by three specific research questions (RQ1, RQ2, and RQ3) and a consequent one (RQ4); these four RQs are defined as follows:

Research question 1: What are the key characteristics, essential elements, and roles of different actors (end-user, platform operator, power provider, etc.) of the basic framework for V2V energy trading?

Research question 2: What are the challenges to developing a V2V energy platform and the current methods for characterising V2V energy trading?

Research question 3: What are the strengths and limitations of the different methods applied to solving those challenges?

Research question 4: What alternative frameworks and methodologies could be developed to overcome the challenges of existing models and approaches in V2V energy trading?

The first research question, RQ1, scopes this review by identifying the structure of the V2V energy trading framework. Research question RQ2 narrows down the scope, focusing on the specific problem to be solved while establishing a V2V energy trading framework and the corresponding methods to address the problems. Research question RQ3 analyses the challenges that V2V energy trading faces on the basis of these problems and corresponding methods. Finally, following the 3 research questions proposed, we defined the research question RQ4 to analyse the alternative frameworks and methodologies that could be adopted while establishing a V2V energy trading framework to overcome the challenges.

2.2. The Literature Searching

This literature review concentrates on identifying projects, frameworks, and research that are relevant to the study of energy sharing and trading among EVs and explicitly excluding unrelated research areas. For research question RQ1, a comprehensive set of keywords was generated, serving as a filter for the literature search and scoping research questions RQ2, RQ3, and RQ4. This search was conducted using various combinations of keywords and logical operators to ensure thoroughness (details in Appendix B, Table A2). We delved into three prominent online databases: Web of Science; ScienceDirect; and Google Scholar. The specific keywords applied in this search are detailed in Table 1.

Table 1. List of keywords used for research question RQ1.

Keywords
EV, electric vehicle, electric car, V2V, vehicle-to-vehicle, vehicular, P2P, peer-to-peer, energy sharing, energy trading

2.3. The Literature Screening

The literature screening process is illustrated in Figure 2. Initially, we extracted a total of 342,000 sources of the literature from the online databases at Stage 1. By applying the exclusion and inclusion criteria at Stage 2, which is described below, we refined the pool of the literature to 1% of the original dataset (give the total). Subsequent screening based on titles and abstracts at Stage 3 ensured that only the literature closely related to our research was considered. Finally, at Stage 4, we selected 61 pieces of the literature that were highly relevant to our study for full review. The detailed flow diagram of this systematic review is attached in Appendix C, Figure A1.

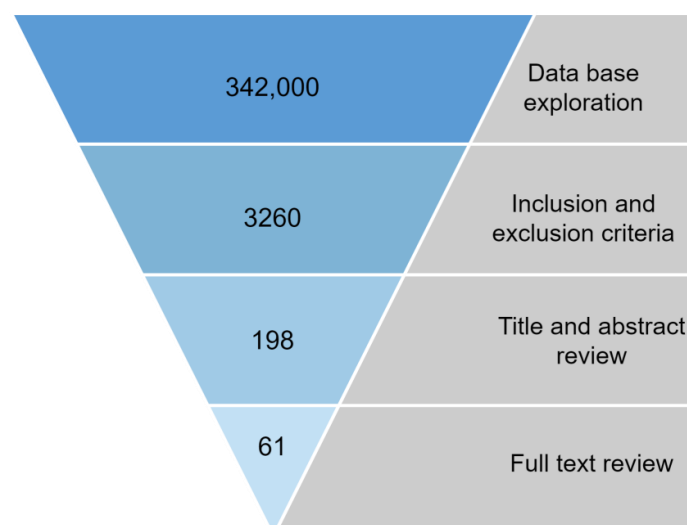


Figure 2. Process of the literature screening with funnel diagram.

Exclusion criteria:

- Duplicate Studies: Any studies that appear as duplicates across the databases searched will be excluded;
- Non-EV Peer-to-Peer Research: Studies focusing on peer-to-peer/P2P energy sharing/trading not specific to electric vehicles/EVs will be excluded;
- Vehicle-to-Grid (V2G) Research: While V2G is related to EV energy management, the literature solely dedicated to V2G without addressing V2V interactions will be omitted;
- Material Science and Chemistry: Research centred on the material science or chemistry of batteries, such as studies on battery materials or electrochemistry, will be excluded;
- Broader Environmental Issues: Studies that primarily address larger environmental issues, like climate change, global warming, or air pollution, will be excluded;
- Non-Article Publications: The literature that does not constitute specific research articles, including journal abstracts, conference indexes, or other compendia of material, will be excluded.

Inclusion criteria:

- Specific subject of Study: Studies specifically focus on vehicle-to-vehicle/V2V energy trading/sharing mechanisms, models, or frameworks within the context of electric vehicles/EVs;
- Peer-to-peer and EV research: Studies concentrate on peer-to-peer/P2P energy trading/sharing in vehicular networks or EV/electric vehicle networks;
- Outcomes of Interest: Studies must report on specific outcomes relevant to V2V energy trading;
- Published Work: Peer-reviewed journal articles, conference papers, and theses/dissertations that are published will be included.

2.4. Information Extraction and Analysis

In accordance with the research questions formulated, the literature was systematically categorised into three primary sections for this review. The first segment, which will be covered in Section 3, aligns with research question RQ1 and is dedicated to examining the construction, operational mechanisms, and key components of the V2V energy trading framework. This section aims to furnish readers with a comprehensive understanding of the framework or model. The second segment corresponds to research question RQ2, which is discussed in Section 4 and delves into the various methodologies or approaches employed within the V2V energy trading framework, including an analysis of the synergistic effects of these approaches. The third segment, answering RQ3 and RQ4, is presented in Section 5 and focuses on identifying the limitations of the reviewed methodologies or approaches and the potential alternative frameworks and methodologies to be developed to overcome the challenges of existing models and approaches in V2V energy trading.

3. Results

3.1. Overview of V2V Energy Trading Framework

In this section, we outline a V2V energy trading framework consisting of four modules, drawing on significant contributions from various studies to the structure of the V2V energy trading framework. Chenghua et al. [34] contributed to the foundational hardware aspects of V2V energy trading, enabling its operational capabilities through Information and Communication Technology (ICT). This work contributes to the ICT module of the outlined V2V energy trading framework. Works from Khizir et al. [35] contributed to how the end-user interfaces with the V2V energy trading framework, discussing the data collection and transaction equipment involved. This provides us with an inspective idea of the end-user module. Alireza et al. [36] explained the pivotal role of the power grid network in linking DERs together, facilitating both energy and information transactions, and contributing to the power grid module. Furthermore, Zhong et al. [37] detailed the construction of an energy trading model at the algorithmic level, including mechanisms to sort and match the participants and decide the clearing transaction price, and contributed

to the foundation of the V2V module. By integrating these contributions, the framework proposed in this paper spans underlying architecture, end-user interaction, as well as hardware and software technologies. This comprehensive framework aims to provide readers with an in-depth understanding of the V2V energy trading framework, highlighting its operations, components, and the intricate interactions between its various elements. Figure 3 exemplifies the architecture of the proposed V2V energy trading framework composed of four critical modules with two local energy markets illustrated [34–37]. Each module is introduced as follows:

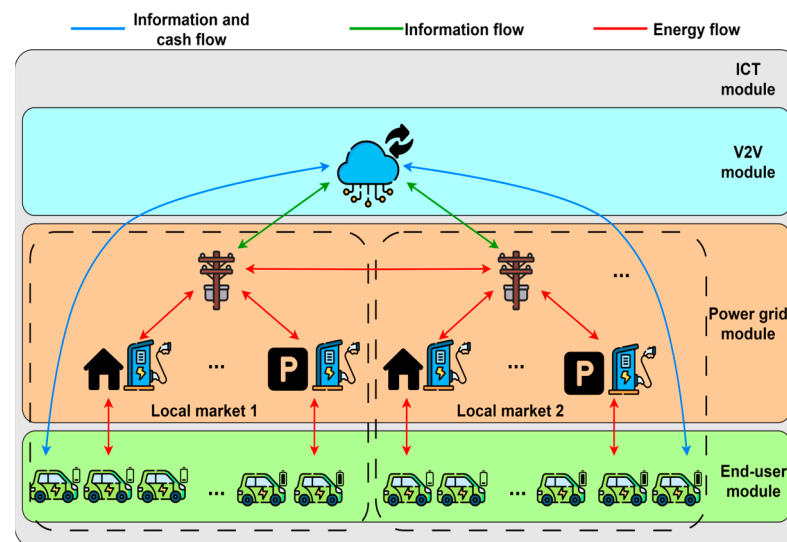


Figure 3. Architecture of V2V energy trading framework. Adapted from [34–37].

The ICT module is composed of communication devices, protocols, applications, and the flow of information [34]. This module constitutes the framework for exchanging information between modules and is the foundation for linking and interacting between all modules. Communication devices encompass sensors, both wired and wireless connections, routers, switches, servers, and different forms of computers [34]. Protocols cover TCP/IP (Transmission Control Protocol/Internet Protocol), PPP (Point-to-Point Protocol), X.25, and more. Communication applications range widely, including tasks like information transfer and file exchange [34]. The information flow pertains to the origins (senders), destinations (receivers), and the specific content of each message that is conveyed among the communication devices [38].

The end-user module in V2V energy trading comprises all entities participating in the exchange, including both buyers (EVs needing electric energy) and sellers (EVs with surplus electric energy). Notably, participants can switch roles between being buyers and sellers depending on their current energy status [25]. This module is rich with essential data and personal information about each participant, such as identity, location, energy consumption patterns, availability of energy for sale or demand, daily routines, and the bid and ask prices for energy transactions [27]. Data acquisition is facilitated through various means, including onboard control terminals, mobile applications, GPS devices, and smart meters installed at authorised electric charging stations [35]. It is paramount that all data collection is conducted with the informed consent and authorisation of the participants to ensure privacy and security. Once gathered, this data is synced with the V2V module, which is responsible for analysing the information to generate actionable insights for the participants. These insights may include data on local energy demand and supply, locations of the nearest charging stations, and current reference prices for energy trading [15]. This information is crucial for enabling participants to make informed and efficient decisions regarding their energy trading activities.

The power grid module encompasses the physical infrastructure of the power system, which includes elements like feeders, transformers, smart meters, electrical loads, distributed energy resources, household chargers, and public charging stations [36]. These components collectively establish the physical distribution network, acting as a link between the end-user module and the V2V module, thereby facilitating V2V energy transactions. Thus, energy exchange primarily occurs between this power grid module and the end-user module, with all traded energy being routed through the power grid module to reach the participants engaged in local energy trading. The power grid module and the V2V module are primarily engaged in the exchange of information [39]. The V2V module utilises data received from the power grid to determine the allocation and distribution of EV energy across various local energy markets.

The V2V module stands at the topmost part of the structure, playing a critical role in defining the allocation and pricing of energy within a V2V energy trading framework. This module is a hub for a variety of business models, platforms, algorithms, and methodologies that facilitate and enhance the trading process. It encompasses pricing and matching mechanisms such as double auctions [40], blockchain technology [21], game theory [30], optimisation methods, and technologies aimed at improving transactions, like energy demand forecasting systems [41].

In the V2V energy trading framework, the V2V module functions as a mediator, organising the exchange of information and financial transactions. It aggregates data from the end-user module, including details on energy supply, demand, expected sell and buy prices (which may be predefined or determined by the trading model), and location [42]. Utilising designated trading algorithms and pricing mechanisms, it aligns supply with demand to identify transaction parties and calculates the financial settlement. Moreover, the V2V module manages cash flows from the end-user module, directing funds from buyers to sellers based on the transaction bill. It ensures that energy corresponding to the transaction is concurrently transferred to the buyer or deducted from the seller. This module also gathers data from the grid module to assess the supply–demand dynamics across different local energy markets [39], facilitating cross-regional energy distribution and mitigating grid pressure during peak demand periods induced by EVs.

Crucially, the information exchange spearheaded by the V2V module is bidirectional. It shares analysed data back to the end-users and (if authorised) to other potentially relevant stakeholders, including charging station operators [43], energy companies or entities, and governments [44]. These data include insights into the local energy market's supply–demand status, daily reference prices for energy transactions, locations of the nearest charging stations, and other pertinent information. This reciprocal flow of information aims to enhance the efficiency of energy distribution and ensure transparency and fairness within the transactions.

The implementation of the V2V energy trading framework encourages multi-dimensional energy transactions within a local geographic area [12], and thus, the massive increase in energy prosumers provides a more decentralised and open electrical network [45]. When short of electrical energy, the conventional V2G model purchases energy from the power grid. However, the V2V energy trading framework introduces an alternative by enabling direct purchases of surplus electricity from other EVs. This framework diminishes the demand pressure on the grid during peak energy consumption periods, encourages the utilisation of distributed energy resources [46], and balances the energy supply and demand relationship in the local energy market [34]. Additionally, the V2V trading model offers economic benefits to its participants [14]. Through negotiations, buyers and sellers have the opportunity to settle on prices that are more favourable compared to transactions with the power grid, presenting a cost-effective solution for both parties involved.

3.2. Challenges for Operationalisation of V2V Energy Trading

From the 61 papers, seven recurrent challenges were identified when characterising V2V energy trading, as shown in Figure 4.

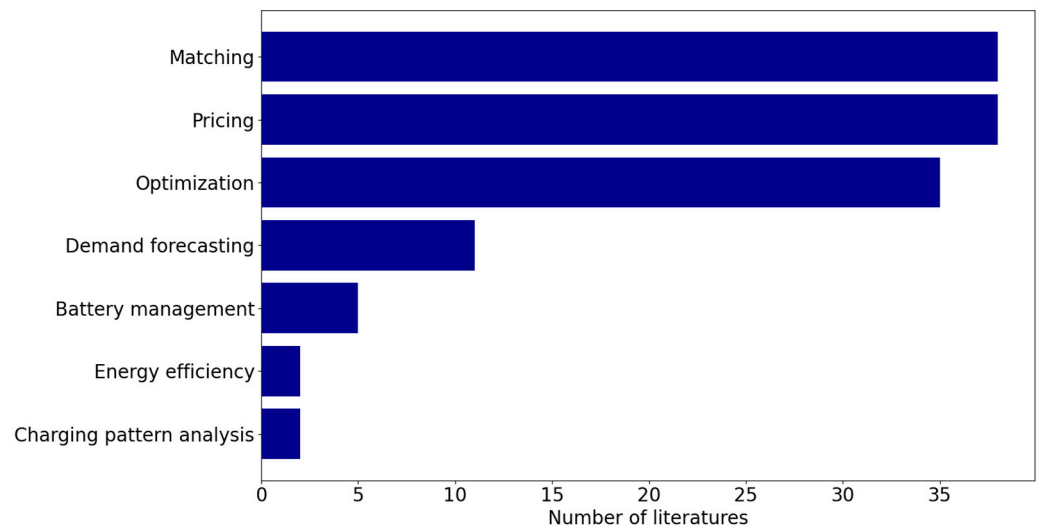


Figure 4. Main challenges to be solved for establishing V2V energy trading framework.

In this paper, we focus on the top four challenges for the following reasons:

1. These four types of challenges collectively account for over 93.1% of all the literature reviewed. As this is a review paper, we aim to cover, as much as possible, in a limited context, the research progress and hotspots in the field of V2V energy trading. We believe that addressing each of these challenges contributes to the successful setup of a trading system, and consequently, the effort to tackle these challenges has spurred the development of a range of innovative methodologies;
2. The four challenges selected for focus in this study have demonstrated significant scientific activity over the past decade, indicating not only a high level of research interest but also suggesting abundant opportunities for further enhancement and innovation, as shown in Figure 5. This figure indicates a shift in research focus over the last decades, moving from hardware development towards commercial and market-related issues. An assumption has been made that the hardware aspects of EVs might have reached a level of maturity due to extensive research and development. Consequently, current research is increasingly centred on exploring economic and commercial dimensions, particularly strategies, to maximise economic benefits for EV owners. This shift reflects a natural progression in the EV industry as it evolves from establishing technological feasibility to optimising market integration and profitability;
3. The challenges excluded from our analysis have yielded fewer studies (10 in total) under the specific keyword screening applied in this paper. This reduction does not inherently imply a lack of research in these areas but may indicate that these topics are not currently prominent within the realm of V2V energy trading research. Despite this, these challenges still hold potential for future research. However, for the purpose of this literature review, we focus on topics that have garnered more discussion within the community, leading to the exclusion of these less-emphasised fields from our current discussion.

To summarise, the key four challenges to be discussed in this paper are as follows:

1. The matching challenge: V2V energy trading involves multiple buyers and sellers. To address this challenge is to develop a rule to decide how buyer and seller could be matched and conduct a transaction. This is the first challenge that needs to be considered in order to conduct V2V energy trading;
2. The pricing challenge: After buyers and sellers have been successfully matched, a clearing price must be determined to complete the transaction. This price needs to take into account the supply and demand relationship in the market and consider

- whether it is profitable for both transaction parties, as well as issues such as fairness and transparency;
3. The optimisation challenge: This challenge involves both the counterparties and the framework operator, aiming to maximise economic benefits and social welfare;
 4. Demand forecasting challenge: Solving this challenge could provide guidance for energy participants to make informed decisions and, hence, support the V2V energy trading framework, including the methods adopted, which would perform better.

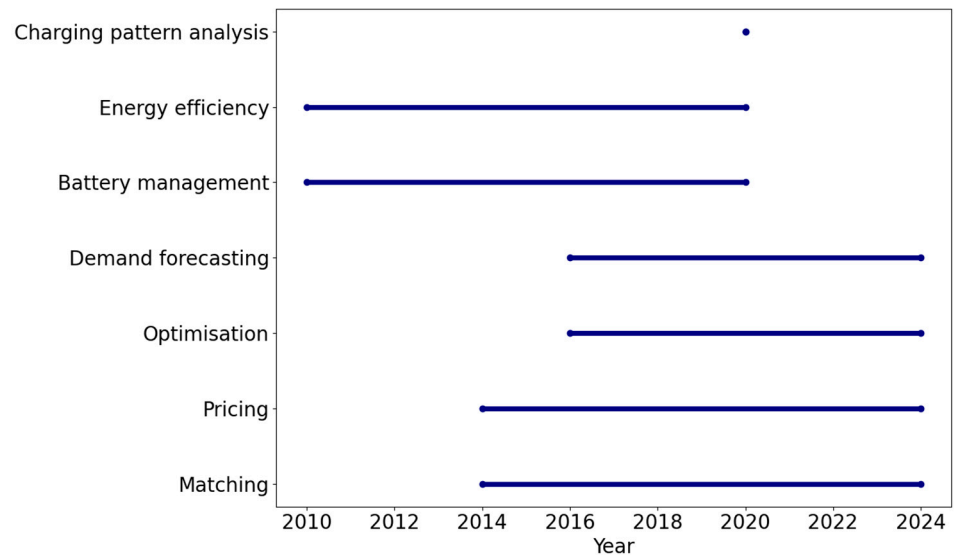


Figure 5. Time distribution of the main challenges in the literature.

Building on these challenges, various methodologies have been proposed, often addressing multiple challenges simultaneously rather than focusing on a single issue. In the next section, we will delve deeper into the selected challenges, exploring the methodological approaches that have been proposed in the existing research and the literature to address them. This analysis will highlight how these challenges have been tackled, showcasing the variety of strategies and solutions that researchers have developed.

3.2.1. The Matching and Pricing Challenges

The matching and pricing challenges within V2V energy trading share a similar distribution of the literature focus. This observation is grounded in the fact that the matching problem and the pricing challenges are intrinsically linked, as matching and pricing challenges are inherently interconnected in much economic behaviour, often leading researchers to address both simultaneously when proposing a new methodology. Consequently, this section merges the discussion of these two challenges, reflecting their interconnected nature and the common approaches employed to solve them in the context of V2V energy trading.

Figure 6 illustrates methodologies from the literature that address the matching and pricing challenges with the related research frequency (detail in Appendix A, Table A1). Within the analysis of the methodologies, three broad categories that include nine methodologies are extracted, as illustrated in Figure 7: the auction-based method, which includes single and double auctions; the blockchain technology, which includes public blockchain, private blockchain, and consortium blockchain; the game theory, which includes Bayesian game, stochastic game, Stackelberg game, and stochastic Stackelberg game.

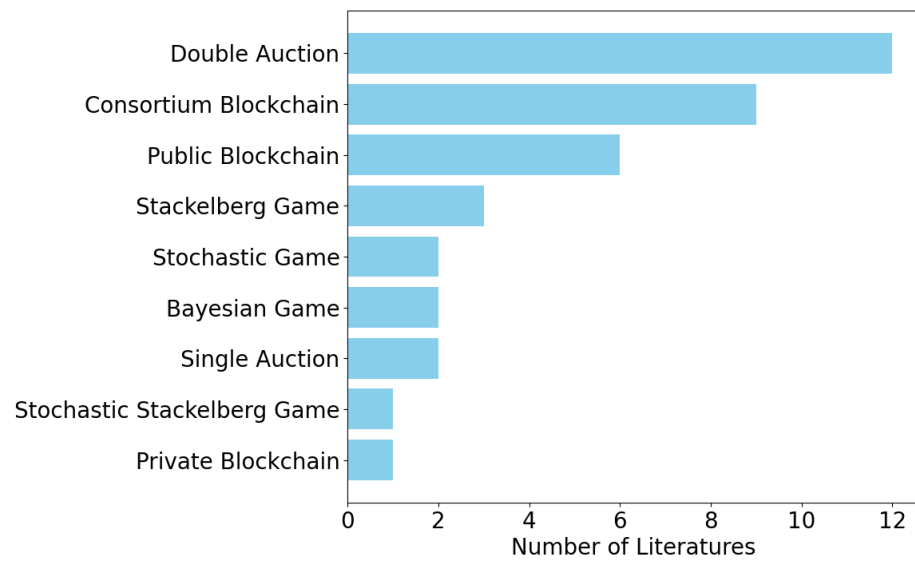


Figure 6. Methodologies for matching and pricing challenges.

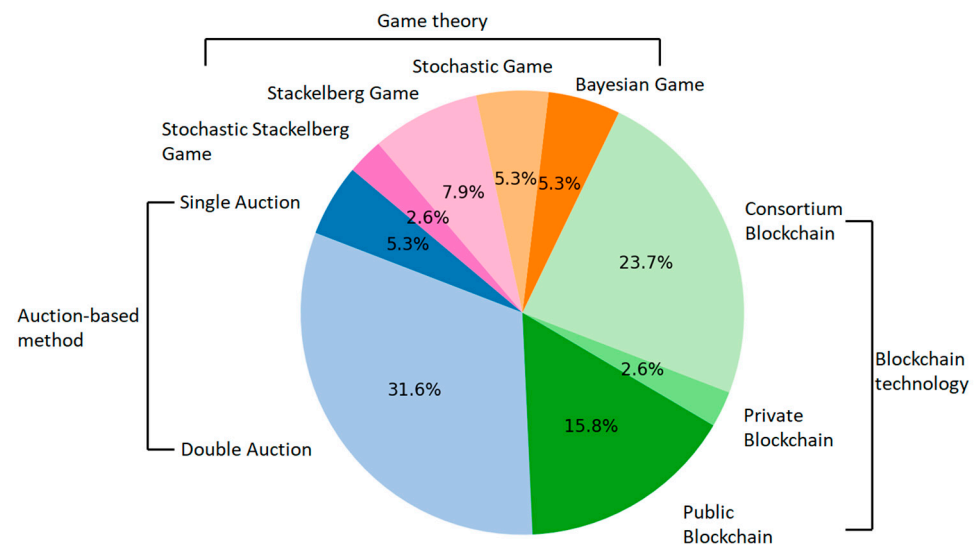


Figure 7. The nine methodologies and the broader categories.

Auction-Based Method

The auction-based method is promising to capture interactions between sellers and buyers in decentralised markets [47]. Auctions in which at least one side of the market consists of a single buyer or seller are single auctions, while two-sided markets in which multiple sellers and buyers may be making bids and offers simultaneously are called double auctions [48].

Zakaria et al. [49] developed a V2V smart contract-based energy transaction system with the reverse auction as a pricing mechanism. In a reverse auction within the V2V energy trading context, the roles of EV consumers (buyers) and EV electricity providers (sellers) are inverted compared to a forward auction, in which a single seller makes an offer, and multiple buyers compete and place bids. Here, once an EV consumer is authenticated, they initiate a request for electricity through the V2V platform’s smart contract specific to their community. Following this, authenticated EV electricity providers enter bids indicating the prices at which they are willing to sell their surplus electricity. As the auction concludes, the EV electricity provider offering the lowest bid is deemed the winner, thus securing the transaction with the consumer. The proposed reverse auction method relies heavily on active participation from EV owners. While the unbalancing of the supply and demand

relationship in the energy trading market frequently occurs, the efficiency of the model is challenged. Umoren et al. [48] introduced a Vickery–Clarke–Groves (VCG)-based single auction to incentivise the energy transactions for EVs distributed within the microgrid. However, the research utilised a linear battery degradation model, which is acknowledged by the authors as potentially oversimplified.

Numerous studies have adopted the double auction method for pricing in V2V energy trading due to its ability to gather both buyers' and sellers' reservation bids/asks and to establish a clearing price beneficial for both parties. Shaomin et al. [50] implemented a double auction-based energy trading scheme enhanced with non-linear regression optimisation aimed at maximising social welfare. A potential limitation is that the research does not deeply explore the economic incentives for both transaction parties, which are pivotal for ensuring high participation and a balanced market. Xu et al., referenced as [25], developed a comprehensive model that employs a double auction as the pricing mechanism for V2V energy trading, demonstrating through a case study that participants can achieve the most cost-effective trading strategy by adjusting the trading price, the available trading time, and the amount of energy traded. The way that manually adjusts the price, time, and amount of energy that accesses the energy trading market does not always ensure optimal economic benefits. An enhanced automated bid and ask algorithm may be a direction for further research. Chenxi et al. [51] introduced a double auction-based peer-to-peer energy trading model that leverages retired EV batteries for energy trading. Long et al. [52] proposed a two-way auction mechanism informed by the Bayesian game theory to address the optimal pricing challenge aimed at maximising the utilities for both buyers and sellers amidst the presence of incomplete information. Their model also integrates the energy trading scheme within a smart contract to ensure transaction fairness and transparency. However, the assumptions of the research about market participant behaviour are simplified. Future work could explore more complex behaviours, including strategic bidding and the impact of incomplete information on the behaviour of the participants. The synergy of double auction mechanisms with smart contract technology is a notable trend, as observed in the works of Zhang et al. [50], Li et al. [53], and Choubey et al. [54], and [50], highlighting the commonality of this approach in addressing issues of transparency and fairness in transactions. Donghe et al. [55] introduced an innovative location privacy-preserving online double-auction scheme for vehicular energy trading. This model is particularly significant for its capability to obscure the actual locations of buyers using a cloaking area, thereby addressing concerns related to privacy in the context of energy trading. Although the proposed double auction scheme aims to incentivise participation through economic benefits, understanding the motivational factors for different stakeholders (EV owners, microgrid operators, and utility providers) requires further investigation. The actual willingness of EV owners to participate in energy trading, considering the potential inconveniences and impacts on their routine, is not addressed.

Blockchain Technology

Blockchain technology represents an approach to enhancing security and decentralising transactions [12,56]. Functioning as a distributed ledger, blockchain securely records and stores critical information, including contracts, data, events, and monetary transactions. This technology ensures transparency and trust by allowing multiple parties to have access to a shared, immutable record of transactions, each encrypted and linked to the previous one, thereby preventing unauthorised alterations and fostering a secure, decentralised transaction environment [56].

Blockchain technology is mainly divided into public blockchain, private blockchain, and consortium blockchain [57–59]. A public blockchain has absolutely no access constraints, and anyone with an internet connection can send transactions to it and become a validator (i.e., participate in the execution of the consensus protocol) [60]. Typically, such networks offer financial incentives to those who follow the rules and utilise some type of proof-of-stake (PoS) or proof-of-work (PoW) algorithm [61]. The best-known and largest

public blockchains are the Bitcoin and Ether blockchains. The most notable application of public blockchain in the field of V2V energy trading is the utilisation of smart contracts. A smart contract executes predefined agreements on the blockchain autonomously, without intermediaries, once certain conditions are met.

The emergence of smart contracts marks a significant research focus within blockchain technology, introduced by Vitalik Buterin et al. [56] and with the launch of Ethereum in 2015. Shengnan et al. [30] introduced a V2V electricity trading scheme based on Bayesian game pricing in blockchain-enabled Internet of vehicles (BIOV). The proposed blockchain ledger records all transactions permanently and accurately. Simultaneously, smart contracts act as pricing agencies. When the transaction occurs, the trading mechanism designed in the smart contract is executed. However, the blockchain framework's scalability and efficiency might not be adequately addressed, especially as the network grows in size. Khan and Byun [62] proposed a peer-to-peer energy trading and charging payment system for EVs. The system employs the Ethereum blockchain to provide a trustful and fair transaction environment for participants and utilises smart contracts for the payment of charging bills through electronic wallets; however, the reliance on blockchain and potentially cryptocurrencies for transactions could introduce volatility and financial insecurity that may affect the system's stability and acceptance [63]. Zakaria et al. [49] developed a V2V smart contract-based system that makes use of Ethereum's blockchain to handle the payment of electricity traded between EVs in a fully automated, transparent, and secure manner. Umoren et al. [64] focused on exploiting blockchain technology to establish a trusted energy trading ecosystem and developing an application to remotely monitor energy trading activities between trading entities. However, this research [64] does not extensively discuss the method for participant incentive. Encouraging adoption among EV owners and other stakeholders requires clear incentives and demonstrating the benefits of participating in the energy trading system. Haiqing et al. [17] established a decentralised power trading model for EVs based on smart contracts in the V2G network. The decentralised transaction model was released to Ethereum, solving the problem of low efficiency and high market influence of the trading centre, and the Pareto improvement is realised through system self-balancing. The author suggests using pseudonyms for transactions, but additional layers of privacy protection may be necessary to safeguard sensitive user data against advanced cypher attacks.

Private blockchains are often referred to as 'permissioned' blockchains [65,66]. It is not possible to join it unless invited by the network administrator. Access is restricted for participants and validators [66]. There are relatively few applications of private blockchains in V2V energy trading. Mohamed et al. [67] proposed a privacy-preserving charging station-to-vehicle (CS2V) and V2V energy trading scheme. The authors leverage the high level of secrecy offered by private blockchains to establish a secure and privacy-preserving energy transaction scheme for V2V and CS2V. The privacy of both charging and discharging EVs, including location, time, and amount of power, are preserved. And an anonymous and efficient payment system that cannot link individual drivers to specific charging locations was introduced to further protect the privacy of EV drivers. However, the technical complexity of blockchain and the proposed privacy-preserving mechanisms might hinder user adoption.

While public blockchains offer transparency and decentralisation [61], they often lack the necessary privacy for many business transactions. Private blockchains, on the other hand, offer privacy but are centralised and restricted to a single organisation [68]. Consortium blockchains provide a middle ground, offering a level of transparency among the consortium members while maintaining privacy from the outside world. Rabiya et al. [18] deployed the consortium blockchain along with the Proof of Authority (PoA) consensus mechanism on the Local Aggregators (LAGs) for secure energy trading for EVs. Smart contracts are introduced to enable fair payments between EVs. The authors developed an incentive mechanism to encourage the EV owner to participate in energy trading and a punishment mechanism to prevent malicious activity. A security analysis was

also carried out, and the proposed consortium blockchain-based system is robust against both double spending and Sybil attacks. While the proposed model emphasises security and privacy through the proposed consortium blockchain-based system, ensuring user privacy without compromising the transparency and accountability of energy transactions could be challenging [69]. Dhaou et al. [70] introduced a decentralised electricity trading framework for EVs in parking lots based on consortium blockchain. An adaptive bidding algorithm named HLProfitX is developed based on machine learning and game theory and integrated into the smart contract, which allows EVs to conduct energy trading with maximum economic benefits using the proposed cryptocurrency HAPPY LIGHT Coin (HLCoin). This contract must be accepted by all participating parties, including sellers and buyers, through the digital signing of an acceptance form at the onset of their connection to the blockchain server located within parking lots. This process ensures that every transaction conducted on the platform adheres to the predefined terms and conditions outlined in the smart contract, facilitating a transparent and secure exchange environment. While the framework proposes using pseudonyms for transactions to protect privacy, the overall security and privacy assurance against sophisticated attacks or data breaches have not been thoroughly addressed [69]. Ayesha et al. [71] developed a consortium blockchain-based trading model. The blockchain is implemented on roadside units (RSUs) to perform secure and fair trading with transparent legal actions. Also, smart contracts are deployed to perform trading actions autonomously among trading parties to tackle trading disputes and facilitate payments to the respective traders. A security analysis of smart contracts is provided as proof that they are secure against all known attacks. The proposed system involves various components such as blockchain, smart contracts, InterPlanetary File System (IPFS) for data storage, and complex privacy-preserving techniques. Ensuring that this system is user-friendly and easily adoptable by both EV owners and energy/data providers may remain a challenge. Muhammad et al. [72] introduced a secure and efficient energy trading scheme for EVs with blockchain technology and a PoW consensus mechanism. In the proposed work, three different smart contracts are introduced to facilitate and secure the energy trading process among EVs and charging stations (CSs). The contract for EVs' registration ensures that all participating vehicles are authenticated and authorised for energy trading. The Energy Smart Contract (ESC) manages data related to charging stations, including the current energy levels and the number of EVs present. The Payment Smart Contract (PSC) is dedicated to securing payment transactions between energy nodes, ensuring that all financial exchanges are transparent and secure. Extensive simulations are performed to prove the efficiency of the proposed work. Another research focuses on reducing the computational cost. While consortium blockchain offers a balance between centralised and decentralised networks by restricting participation to only authorised nodes, scaling the system to accommodate a large and dynamically changing number of EVs and CSs could pose challenges. Yingsen et al. [21] proposed a distributed V2V Energy Trading Blockchain (ETB) structure with the Hashgraph-based Block Alliance Consensus (BAC) algorithm. The proposed BAC reduces the time complexity of traditional Byzantine Fault Tolerance to $O(N)$, where N is the number of EVs. The author claimed that BAC can significantly improve the throughput and security of ETB like Hashgraph, support the dynamic addition and deletion of nodes, and prevent the V2V ETB from Sybil Attack in a large-scale network. While the proposed system aims to address security through blockchain and the BAC mechanism, a deeper analysis of privacy concerns, particularly regarding the tracking and sharing of EV energy usage and trading data, is necessary.

Game Theory

Game theory offers a robust mathematical framework for modelling and analysing the strategic interactions among autonomous agents [73], such as EVs, that have competing interests. This framework is important in the context of V2V energy trading systems, where it facilitates the understanding and prediction of participants' behaviours under various scenarios. Game theory can serve as a standalone mathematical foundation for

designing and implementing V2V energy trading strategies [15], or it can be incorporated as a component of other technological solutions, including the use of smart contracts within blockchain technology, to establish and enforce trading rules. This section delves into the application of game theory to V2V energy trading, highlighting how various game theory algorithms can be tailored to optimise trading outcomes.

Researchers in [19,53,74] concentrate on cooperative game theory. Mohammed et al. [19] introduced a two-module matching algorithm for optimal cooperative V2V energy transactions. The first module employed the Gale–Shapley game to produce stable matchings for energy transactions between the EVs with consideration of their individual rationality, and the second module introduced the user satisfaction model. Extensive simulation with a real-life dataset is conducted, and the result shows that efficient and effective V2V stable matches are obtained. The utilisation of the Gale–Shapley algorithm requires a complete ranking of preferences from all participants. However, in practice, obtaining accurate and comprehensive preference lists from EV owners might be challenging. Zugang et al. [53] proposed an EV P2P energy trading model and determined the P2P transaction electricity price based on cooperative games. Promiti and Albert [74] introduced a game theoretic approach to offering participation incentives for V2V charge sharing. The authors utilise Nash Bargaining theory to show that participation in the network can yield profits for the seller driving to their destination, and that can increase the number of cars reaching their destination without needing to stop for recharging. However, the game–theoretic approach adopted in this paper may not adequately capture the dynamic nature of EV usage.

Other pieces of research focus on the application of non-cooperative games. Xinyi et al. [75] introduced a basic situation of V2V energy trading on the Internet of vehicles (IoV). By formulating the model as a Stackelberg game, the authors prove the existence of a unique Nash equilibrium for the game and derive its analytical results. Their results show that the Stackelberg game can maximise the payoffs of both buyers and sellers through constant price adjustments. The proposed model focuses on a simplified one-to-one trading scenario. However, real-world implementation would involve multiple buyers and sellers interacting simultaneously; hence, the Stackelberg game may not simulate the real-world situation properly. Shubhani and Neeraj [76] proposed a theoretical game-based model to explore the interactions between EVs and service providers (SP), i.e., smart grids and service consumers in smart grid systems. The presented Stackelberg game theory scheme is a one-leader, multi-follower scheme, where SP is the leader, and EVs are the followers. Simulation results demonstrate that the proposed scheme outperforms the existing state-of-the-art schemes using various performance evaluation metrics. The model's effectiveness relies on the availability and accuracy of information about other players' strategies, costs, and preferences. Nevertheless, in reality, participants often have incomplete or imperfect information, which can lead to suboptimal decisions and outcomes. Hayla et al. [77] developed a pricing-based incentive consensus mechanism, PPoR (Practical Byzantine Fault Tolerance-based POR), based on a Stackelberg game model to motivate energy transaction validators involved in the blockchain-enabled energy trading (BET). The proposed incentive mechanism rewards monetary values and allocates mining values to the validator EVs in order to encourage honest and cooperative nodes. The simulation results show that the proposed method improves throughput, transaction latency, and utility optimisation in the V2V energy trading. However, the effectiveness of the economic incentive mechanism and its impact on the behaviour of EV owners, particularly in terms of encouraging energy selling and buying activities, warrants further empirical study.

Dhaou et al. [70] adopted a stochastic bidding process for the proposed distributed smart contract solution for V2V energy sharing. Numerical simulations were conducted to prove the effectiveness of the proposed solution. Yue et al. [78] introduced a stochastic Stackelberg games (SSG) approach to energy trading between residential microgrids (MGs) and plug-in EVs, incorporating stochastic variables for EVs. They proved the existence and uniqueness of the SSG equilibrium. Simulation results demonstrated that energy sharing coordinated through SSG could significantly reduce the total cost for MGs compared to

traditional trading with the utility grid. Their study rigorously derived the equilibrium solution for both sellers and buyers, highlighting the efficiency and cost-effectiveness of the SSG model in microgrid energy trading. However, this model assumes that all participants in the MG ecosystem, both sellers (MGs) and buyers (EVs), will act rationally to maximise their own utilities. This simplification may not accurately capture real-world decision-making processes.

Shengnan et al. [30] applied Bayesian game theory to transaction pricing in a V2V electricity trading scheme for the BIoV, addressing the challenge of incomplete information within the network. Their method aims to maximise utility for both electricity buyers and sellers by designing a pricing mechanism that achieves optimal pricing at linear strategic equilibrium. The transaction volume is determined by solving a convex problem that maximises social welfare. Numerical results validate the effectiveness and feasibility of their proposed trading scheme, demonstrating its potential in scenarios where precise information is lacking. Yue et al. [15] introduced a V2V Energy Trading in Residential Microgrids (VETRM) model, with the adoption of a Bayesian game trading model considering the information uncertainty of the participants. The probabilities of different types of combinations are used to evaluate the roles of both parties in the game, from the perspective of EVs, to maximise their profits and coordinate energy distribution. Simulation experiments have verified that users who use the proposed transaction model to participate in V2V power transactions can obtain complacent profits from traditional power grid transactions, reduce the total cost of the power grid, make the energy distribution more reasonable, and reduce the energy loss. This model incorporates stochastic elements to account for uncertainties in EV behaviour and renewable energy generation. However, the adaptability of the model to unforeseen changes in technology, market conditions, or participant behaviour could be further analysed.

3.2.2. The Optimisation Challenge

The utilisation of optimisation methods plays a crucial and foundational role in V2V energy trading, with over 57% of the 61 reviewed papers employing optimisation in their methods. Primarily, optimisation techniques are adopted to maximise the economic benefits or social welfare of participants involved in energy trading. Additionally, some studies leverage these methods to minimise energy losses during trading or to ensure a balance between supply and demand. Given the extensive adoption of optimisation algorithms across the literature, this section will focus on discussing a selection of the most representative studies to provide insights without repetitive analysis.

Yassine and Hossain [79] developed a match maximisation mechanism among EVs to increase their social welfare and energy trading volume. The proposed match maximisation problem aims at increasing trading volume and providing suitable energy allocation for V2V charging while considering the number of transactions. Simulation shows that volume maximisation can produce considerable matching pairs where EVs achieve average positive utilities. However, the proposed system relies heavily on the Internet of vehicles (IoV) and fog computing infrastructure to facilitate communication and energy trading between EVs. The reliability of such communications in different environments, particularly in less-urbanised or more geographically challenging areas, could limit the effectiveness of the proposed model. Gang et al. [80] introduced an optimal energy trading scheme for plug-in hybrid electric vehicles (PHEV) based on fog computing. This architecture includes a fog computing energy centre (FCEC), which manages local energy trading and reduces the peak load energy trading for an external public energy company. The authors modelled the optimisation problems for energy trading under two different types of FCECs: (1) a nonprofit-driven FCEC whose goal is solely to benefit the PHEV charging and discharging operations; and (2) a profit-driven FCEC whose goal is to maximise its own profits while still guaranteeing that each PHEV achieves a nonnegative utility. Algorithms for these two types of FCECs to seek optimal pricing and make supply–demand decisions are presented. Simulation results show that the proposed algorithms are superior to existing

algorithms in terms of the convergence rate, the final objective value, and the evenness of the Pareto solution set. While the proposed fog computing-based architecture and optimisation models theoretically enhance the efficiency of energy trading among PHEVs, their practical implementation may face challenges due to the complex dynamics of real-world traffic and energy demand patterns that are not fully captured in simulation environments. Xiaohong et al. [81] proposed an optimal charging scheduling algorithm for hybrid vehicle charging scenarios. A multi-objective optimisation was established with consideration of two aspects: to maximise the user's satisfaction and minimise his/her cost. Beyond considering the basic electricity demands and supplies, the algorithm integrates various metrics, such as the locations of charging and discharging entities, the waiting times of discharging entities, and the driving speeds of EVs, among others. To address the optimisation model, an enhanced version of the Non-dominated Sorting Genetic Algorithm (NSGA) is proposed. Experiments were conducted using real charging data, comparing it against other algorithms (TPMA and the proposed scheduling algorithm) across different scenarios such as V2G, V2V, and a hybrid scenario developed in this study and varying proportions of discharging entities (charging stations, Mobile Charging Vehicles (MCVs), and discharging EVs). The results show that the proposed scheduling algorithm has good performance in terms of user satisfaction and user cost from different points of view. However, frequent charging and discharging can affect battery lifespan [82]. The economic and environmental impacts of accelerated battery degradation due to increased participation in V2V and MCV2V optimisation have not been thoroughly investigated. Ameena et al. [16] investigated the effect of EVs and shiftable loads on P2P energy trading with enhanced Vehicle to Home (V2H) mode and proposed an optimised Energy Management System aimed at reducing the net energy exchange with the grid. Mixed-integer linear programming (MILP) is used to find optimal energy scheduling for smart houses in a community, considering the load scheduling, which reduces the energy cost and makes the best use of PV energy by shifting appliances to the times when the PV energy is surplus or to the off-peak/ mid-peak times. The lifetime of the battery storage system (BSS) and EV batteries is also considered by including their degradation costs in the optimisation problem. MILP is known for its computational intensity, especially as the size of the problem increases [83]. This paper addresses a community with smart houses, including EVs and shiftable loads. As the number of houses, EVs, and the complexity of scheduling tasks increases, the computational burden could become a significant challenge, potentially limiting the real-time applicability of the proposed system.

3.2.3. The Demand Forecasting Challenge

The forecasting of future energy demand in the energy trading market has been increasingly noticed after the widespread use of artificial intelligence (AI) techniques and has become a hotspot in the research field of V2V energy trading. By extracting the charging or driving pattern of the EV driver from the dataset, the pattern could be fed to the machine learning or deep learning model to learn and forecast the future energy demand. Energy demand forecasting can provide an effective reference for matching energy supply and demand, scheduling, and decision-making by energy trading participants [84], so the application of this technology is a valuable research direction.

Tianyu et al. [9] developed a deep learning-based approach for short-term probabilistic forecasting of EV charging demand, aimed at predicting the future demand quantiles at a charging station 5 min ahead. This study highlighted two primary factors influencing the charging behaviours of plug-in EVs: (1) the user's living habits; and (2) the user's stochastic behaviour at the current timestamp. Their model integrates both historical charging habits and the current trend of charging demand variations, employing the Machine Theory of Mind (MToM) framework. This innovative approach ensures a comprehensive analysis by considering both regularities in user behaviour and spontaneous demand fluctuations. The effectiveness of this model was demonstrated through two case studies using real EV charging demand datasets, where it outperformed existing state-of-the-art models in the

accuracy and reliability of charging demand prognostics. However, the model is trained and validated on datasets from specific charging stations (Caltech and JPL). Its ability to generalise across different regions, cultures, or user behaviours without additional calibration remains uncertain. Mariz and Sungwoo [85] introduced a forecasting model designed to predict EV charging demand utilising big data technologies. This model leverages historical traffic and weather data from South Korea. The forecasting methodology encompasses several key processes: cluster analysis for categorising traffic patterns; relational analysis to pinpoint factors influencing EV charging demand; and decision tree algorithms for defining classification criteria. This model particularly focuses on variables such as the charging start time, which correlates with real-world traffic patterns, and the initial SoC of the EV battery. To demonstrate the practical application and effectiveness of their forecasting model, the authors provided case studies illustrating EV charging demand for both weekdays and weekends across different seasons—summer and winter. These case studies highlighted the variance in charging load profiles at residential and commercial sites, showcasing the model's capability to accurately forecast EV charging demands under diverse conditions. Meanwhile, by relying primarily on historic traffic patterns and weather data, the model may overlook other significant factors affecting EV charging demand, such as changes in electricity prices, the availability of charging infrastructure, or special events. Amini et al. [86] developed a forecasting model for EV charging demand using the autoregressive integrated moving average (ARIMA) approach. This model is designed to predict electric power consumption, encapsulating both conventional electrical load (CEL) and charging demand of EVs (CDE). In their EV parking lot model, they applied a probability density function (PDF) for arrival and departure times derived from historical data. To accommodate varying driving patterns, expected driven distances were calculated using the PDF of daily driven distance data. The ARIMA model parameters were fine-tuned with historical load point data to achieve an optimal root mean square (RMS) error. This model's effectiveness was demonstrated using two test systems—the 6-bus and IEEE 24-bus test systems—for power system scheduling. The model's proficiency for day-ahead scheduling was validated by rescheduling the power system in real-time operation with historical data, followed by an evaluation of the rescheduling cost. Simulation results indicated that this decoupled CEL/CDE ARIMA-based forecasting model yielded more accurate demand predictions than traditional integrated forecasting strategies. However, the focus on short-term forecasting (5 min ahead) in this paper may not fully meet the needs of power system operators or charging station managers who require longer-term (one day ahead or longer) forecasts for strategic planning and infrastructure development. Qiang et al. [87] introduced a novel EV charging demand forecasting model leveraging online ride-hailing trip data, marking a significant advancement in EV charging demand modelling. This approach integrates online ride-hailing trip data, offering a more streamlined and efficient method compared to traditional taxi data-based models by reducing data redundancy and simplifying the data cleaning process. By utilising open-source trip datasets, the authors efficiently extracted essential data and rules, such as residents' trip distribution, traffic origin–destination (O–D) matrices, and actual driving routes, addressing the challenge of accessing real traffic data. The model accurately reflects real-world driving and charging behaviours by carefully selecting and setting EV driving and charging parameters. Furthermore, it conducts an in-depth analysis of regional variations in charging demand and load transfer characteristics, laying the groundwork for future studies on charging guidance and impact assessment. To evaluate the effectiveness of their model, the authors designed four charging scenario groups: (1) charging demand load in functional areas; (2) demand load under different path planning methods; (3) demand load influenced by varying charging facility service rates; and (4) demand load affected by different fast/slow charging ratios. The model's validity was confirmed through path planning experiments and analysis of the spatial–temporal distribution of EV charging demand loads across these scenarios, demonstrating the proposed method's practical applicability and effectiveness in forecasting EV charging demands. This paper focuses on EV charging demand forecasting without

explicitly addressing how these forecasts integrate with or impact broader energy systems, such as the electrical grid's capacity to meet peak charging demands or the potential for integrating renewable energy sources. Gilles et al. [88] proposed a day-ahead charging demand forecast of EVs with a time resolution of 15 min using a deep neural network. The forecast algorithm is based on long short-term memory (LSTM) neural networks, and additional features such as calendar and weather features are included in order to help the neural networks capture the variabilities in daily EV charging demand. The neural networks are tested on a difficult use case of a hospital charging site. The results show great performance despite the high variability and the high stochastic behaviour of the EV charging demand pattern with an MAE lower than 1 kW. However, the approach involves detailed data processing and complex deep learning techniques, which may require significant computational resources for data analysis, pattern recognition, and simulation. This could pose challenges for real-time applications as the calculation and response process could be time-consuming.

4. Discussion

This section answers the research questions Q3 and Q4 to identify the research gaps that exist among the different methods applied to solving the challenges when developing a V2V energy trading framework and discuss the alternative frameworks and methodologies that could be developed to overcome the identified gaps of existing models and approaches in V2V energy trading.

4.1. Gap in the Knowledge

In this section, we explored the knowledge gap from two perspectives. Firstly, we delved into specific technological aspects, discussing the existing gaps and limitations identified in the reviewed literature. Secondly, we expanded our scope by applying the PESTEL framework to identify unexplored or underexplored areas within the existing body of the literature. The research into addressing the matching and pricing challenge forms a foundation for establishing a V2V energy trading framework. The adoption of auction-based methods is particularly noteworthy for capturing the interactions between buyers and sellers [45]. This approach facilitates negotiation, allowing for the emergence of prices made by participants that most accurately reflect the true market conditions driven by supply and demand. Moreover, the nature of auction-based methods promotes fairness and transparency within the trading environment, ensuring that prices are determined in a manner that is equitable for all participants [14,40,51]. Single auctions adopted by Umoren et al. [48] and El Houda et al. [49] facilitate one-to-many transaction scenarios, accommodating either a single seller with multiple buyers or a single buyer with multiple sellers (reversed auction). However, within the energy trading market, where transactions are frequent and simultaneous trading desires from multiple sellers and buyers are common, single auction systems might struggle with efficiency due to the increasing number of participants and transactions, potentially leading to inefficiencies in the auction process [89,90] and a high number of unsuccessful auctions. Double auctions emerge as a viable solution to address this issue by allowing for simultaneous bids from both buyers and sellers, enhancing efficiency in scenarios with frequent and multiple-participant transactions. Nevertheless, double auctions face their own set of pricing challenges. In traditional double auctions, as discussed by [14,50,51,72], a final clearing price is shared among all participating buyers and sellers. This arrangement can lead to issues such as sellers potentially manipulating the final clearing price by underreporting the amount of energy submitted to the local energy trading market [91–93]. To address this specific gap, study [93–95] introduces the trade reduction method. This approach aims to mitigate the problem of sellers manipulating prices by attempting to balance the market. This approach excludes the closest bids to the market clearing price to ensure a more equitable transaction price, albeit at the cost of excluding certain participants from the trading process. However,

in this approach, the bids and asks that are closest to the final clearing price from a matched buyer and seller pair are unable to participate in the trade [93].

Blockchain technology brings privacy and security to V2V energy trading; however, ensuring the security of blockchain remains a significant challenge [40,88,89]. Studies such as [18,21,49,67,71] have demonstrated through simulations that the proposed blockchain models could withstand most types of attacks. Well-known blockchain models, like Bitcoin, have also been shown to provide robust security measures. However, other blockchain frameworks, such as Ethereum, have historically been vulnerable to multiple attacks [96]. This resilience against attacks is particularly critical for applications within essential infrastructure sectors, especially energy systems [97]. Another significant challenge for blockchain technology lies in the development cost [98]. Although blockchain has the potential to offer considerable cost savings by eliminating the need for intermediaries, the PoW consensus mechanism employed by some blockchain networks is notably energy-intensive. This high energy consumption stems from the requirement for substantial computing power to solve complex mathematical puzzles. Additionally, within applications in energy trading, the integration of blockchain technology with existing smart meters and grid infrastructure entails considerable costs [99], and the additional costs of storing data in an ever-expanding ledger cannot be ignored. Transaction speed and throughput are other inevitable challenges that blockchain technology is facing [100]. As the volume of transactions escalates, the time and resources needed to process and validate each transaction can increase dramatically. For instance, Bitcoin is limited to processing approximately 7 transactions per second (tps), and Ethereum can handle about 15–30 tps [101]. This performance is markedly slower when compared to traditional payment systems, such as Visa, which can manage thousands of transactions per second [102]. This discrepancy underscores a significant bottleneck for blockchain networks, especially in applications requiring high transaction volumes and fast processing times, such as financial services and energy trading.

Game theory is a powerful mathematical framework used in V2V energy trading to model complex interactions under uncertainty, dynamism, and hierarchical decision-making [74,103,104]. Especially when game theoretic methods are integrated into smart contracts in blockchain technology, the privacy and security of the V2V energy trading framework are also guaranteed. The application of Bayesian games provides a paradigm for counterparties to trade with incomplete information [74]; however, the effectiveness of Bayesian games hinges on the assumption that all players are rational and will update their beliefs and strategies optimally [105,106], which may not always hold true in real-world energy trading market. Stochastic games consider state transitions that are influenced by the actions of all players [107]. The state space can become very large, making the game difficult to analyse and solve, and the calculation and response progress could be time-consuming. These games often rely on the Markov property, which assumes that future states depend only on the current state and actions [108]; however, the historical context is highly relevant to the action that EV owner could take. For instance, a successfully traded and fully charged EV user is unlikely to have energy demands over the next few days. At the same time, The Stackelberg model's leader–follower dynamics might not accurately capture the flexibility and negotiation possibilities in real-world V2V energy trading, where roles can be more fluid. The research on multi-leaders and followers may address this problem [109].

Finally, there are still gaps that need to be addressed in demand forecasting. Existing models have not yet achieved sufficient accuracy due to the fragmented and irregular nature of EVs' charging and discharging behaviours [39]. Contemporary studies have focused their forecasts on future power (kW), which makes the forecasts much more accurate. However, forecasting the total amount of energy demand (kWh), the start time, and the end time is essential if demand forecasts are to better guide traders involved in V2V energy trading, as this level of detail is crucial for providing actionable insights to traders in V2V energy trading, enabling more efficient and effective decision-making [41,46]. However, the accuracy of forecasts in this area still falls short of the necessary precision.

Table 2 presents a PESTEL analysis of the reviewed methodologies. The keywords we used to screen the literature, corresponding with exclusion and inclusion criteria that we defined, made our systematic review mainly focus on technological research. Hence, all methodologies encompass the Technological factor. The Political and Legal factors are outside the scope of our review, as these factors do not significantly impact the technical dimensions we are investigating. Notably, the majority of methodologies address the Economic factor, reflecting a primary motivation for employing the V2V energy trading framework due to its potential for significant economic benefits. However, the demand forecasting method, which is an AI technology designed to enhance the performance of the V2V framework, indirectly contributes to economic benefits and, thus, does not directly cover the Economic factor at a high level. Most methodologies also consider the Social factor, as they are originally designed and oriented to enhance social welfare through various aspects, including economic benefits, participant beliefs, lifestyle trends, and attitudes towards technology. We discovered a significant gap concerning the Environmental factor in the research reviewed. The reviewed literature inadequately covers this aspect, with only 9% of auction-based methodologies addressing it. It is important to note that our findings do not suggest a lack of research covering the Environmental factors. Rather, it highlights a need for future research, specifically on V2V energy trading, to increasingly address environmental impacts, such as quantifying reductions in carbon emissions through V2V applications, utilising natural resources in a more efficient way, and evaluating the effects of climate change, particularly as DERs like PV and wind power generation are notably affected by climatic conditions.

Table 2. PESTEL analysis of the reviewed methodologies.

Methods	Factors					
	Political	Economic	Social	Technological	Environmental	Legal
Auction-based methodology	-	100%	73%	100%	9%	-
Blockchain technology	-	100%	87%	100%	0%	-
Game theory	-	100%	88%	100%	0%	-
Optimisation	-	100%	100%	100%	0%	-
Demand forecasting	-	18%	67%	100%	0%	-

4.2. Alternative Frameworks and Methodologies for Future Work

When addressing matching and pricing challenges, it is crucial to enhance the economic benefits of participants in V2V energy trading by increasing the efficiency of matching and determining optimal prices. The integration of smart contracts with matching and pricing mechanisms such as auction-based systems and game theory represents a promising approach, and further exploration is worthy of being carried out. A possible research direction is to develop game-theory models that can characterise the complexities of dynamic interactions and incomplete information within V2V networks. For example, the application of adaptive and evolutionary game models [110] can adapt to participants' changing preferences and strategies over time. In the meantime, research by B Ding et al. [111] indicates that the Nash bargaining model could be an efficient approach for maximising the profits of the cooperative energy system and each engaged participant.

Addressing the high computational demands and energy consumption of blockchain technology is another possible research direction, particularly for applications like V2V energy trading that require efficient and sustainable operations. Traditional Proof of Work (PoW) mechanisms, while secure, are notoriously energy-intensive due to their reliance on solving complex mathematical puzzles [112]. As a more sustainable alternative, Proof of Stake (PoS) offers a significant reduction in energy and computational requirements [113]. In PoS, nodes are selected to validate transactions based on their holdings of the network's currency, which aligns validation power with stakeholding rather than computational work, thereby drastically reducing the energy needed. Building on PoS, Delegated Proof of Stake (DPoS) introduces a layer of democratic governance, where stakeholders vote on delegates to perform the network's validation work. This not only maintains security and

decentralisation but also enhances transaction processing efficiency and reduces energy usage by limiting the number of nodes involved in the consensus process [113]. Proof of Authority (PoA), another alternative, offers a more centralised approach where transaction validation is performed by approved accounts or validators. This method is particularly well-suited to permissioned blockchain environments, where it can ensure high throughput and scalability while maintaining control over the validator pool. By reducing the number of nodes required for consensus, PoA can significantly decrease the computational and energy costs associated with more decentralised blockchain mechanisms [114]. These consensus mechanisms, PoS, DPoS, and PoA, present viable alternatives to PoW, providing energy-efficient solutions that can enhance the sustainability of blockchain-based systems used in V2V energy trading [114].

Regarding the optimisation challenges, the adoption of digital twin technology [115] presents a novel research direction. Digital twins can simulate the V2V energy trading environment, facilitating the testing and optimisation of trading strategies and system performance under a variety of conditions. This approach allows for the potential problems to be identified and trading mechanisms to be refined in advance of the widespread deployment of V2V trading frameworks.

Given that EV charging and discharging behaviours often follow time-sequenced patterns, sequential forecasting models like long short-term memory (LSTM) [41], Gated Recurrent Units (GRU) [116], or comprehensive frameworks combining Convolutional Neural Networks (CNN), LSTM [117], and Attention models [118] could improve future demand forecasting. Additionally, the application of AI technology in V2V energy trading could extend beyond demand forecasting to include strategy development and decision-making processes. Reinforcement learning [119], for example, could be an alternative framework used to devise strategies on when and how much energy to buy or sell and at what price to achieve optimal economic benefits. Furthermore, addressing the problem of privacy and massive calculation consumption associated with the deployment of large machine learning or deep learning models has become a worthwhile research direction for the future. A possible solution is the adoption of federated learning [120], which provides a method for training machine learning models across decentralised devices or servers without data exchange, enhancing privacy, reducing reliance on centralised data collection, and minimising computational demands for large-scale machine learning and deep learning models.

4.3. Review Limitations

In this research paper, we acknowledge the presence of potential limitations in our study. One such limitation is the risk of selection bias, which may arise from the constrained use of keywords in selecting the relevant research literature. The choice of keywords and, consequently, the selection of the literature was significantly influenced by a single reviewer's perspective, which could have impacted the breadth and diversity of the studies included in our review [121]. It is also acknowledged that the screening of studies by a single reviewer might have had an effect on the results, potentially excluding relevant studies [122].

Additionally, the fields of V2V energy trading, along with the technologies of blockchain and machine learning that are critical to this domain, are rapidly evolving. This dynamic nature means that even recent systematic reviews can quickly become outdated as new research findings and technological advancements emerge. Furthermore, the reliability of our review's conclusions may be influenced by the quality of the studies included [32]. Variations in study designs, the populations examined, and the outcomes measured across different studies bring challenges for comparing results or aggregating findings coherently.

5. Conclusions

In this paper, we conduct a systematic review of the V2V energy trading framework, detailing its structure and identifying methods used in current research, the challenges

faced, and suggesting potential future research directions. Our aim is to provide insights into the concept of V2V energy trading for researchers. The contributions of this paper are as follows:

1. This paper offers a comprehensive review of V2V energy trading frameworks. We examine the V2V energy trading framework in depth, covering its key characteristics, essential elements, the roles of different actors (end-user, platform operator, power provider, etc.) in establishing this framework, the methodologies used in current research, the challenges of current research, and future research directions. To our knowledge, this is the first review paper focused specifically on the V2V energy trading;
2. This paper provides a detailed summary of the most commonly faced challenges in current V2V energy trading research. This includes an in-depth analysis of several critical problems that need resolution within the V2V energy trading framework, with a focus on four of the most frequently discussed and representative problems. Moreover, this paper organises the range of methodologies proposed to tackle these challenges, encompassing topics such as auctions, blockchain, game theory, optimisation, and demand forecasting. It further examines how these methodologies interact and combine, offering researchers a comprehensive overview of the current method utilised;
3. This paper outlines future research directions and potential priorities for the development of the V2V energy trading frameworks. It anticipates the future integration of advanced technologies, such as AI and digital twins, and more established technologies, like smart contracts, into the V2V energy trading.

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Appendix A

Table A1. Methodologies for matching and pricing.

Methodologies	Articles
Single Auction	[48,49].
Double Auction	[25,50,51,53–55,79,123,124].
Public Blockchain	[17,30,49,56,62,64].
Private Blockchain	[67].
Consortium Blockchain	[18,21,50,70–72,81,122].
Bayesian Game	[15,30].
Stochastic Game	[70,78].
Stackelberg Game	[75–77].
Stochastic Stackelberg Game	[78].

Appendix B

Table A2. Keywords and logical operators for the literature screening.

(EV OR “electric vehicle” OR “electric car” OR V2V OR “vehicle-to-vehicle” OR vehicular OR ((P2P OR “peer to peer”) AND (EV OR electric vehicle OR electric car))) AND (“energy sharing” OR “energy trading”)

Appendix C

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources

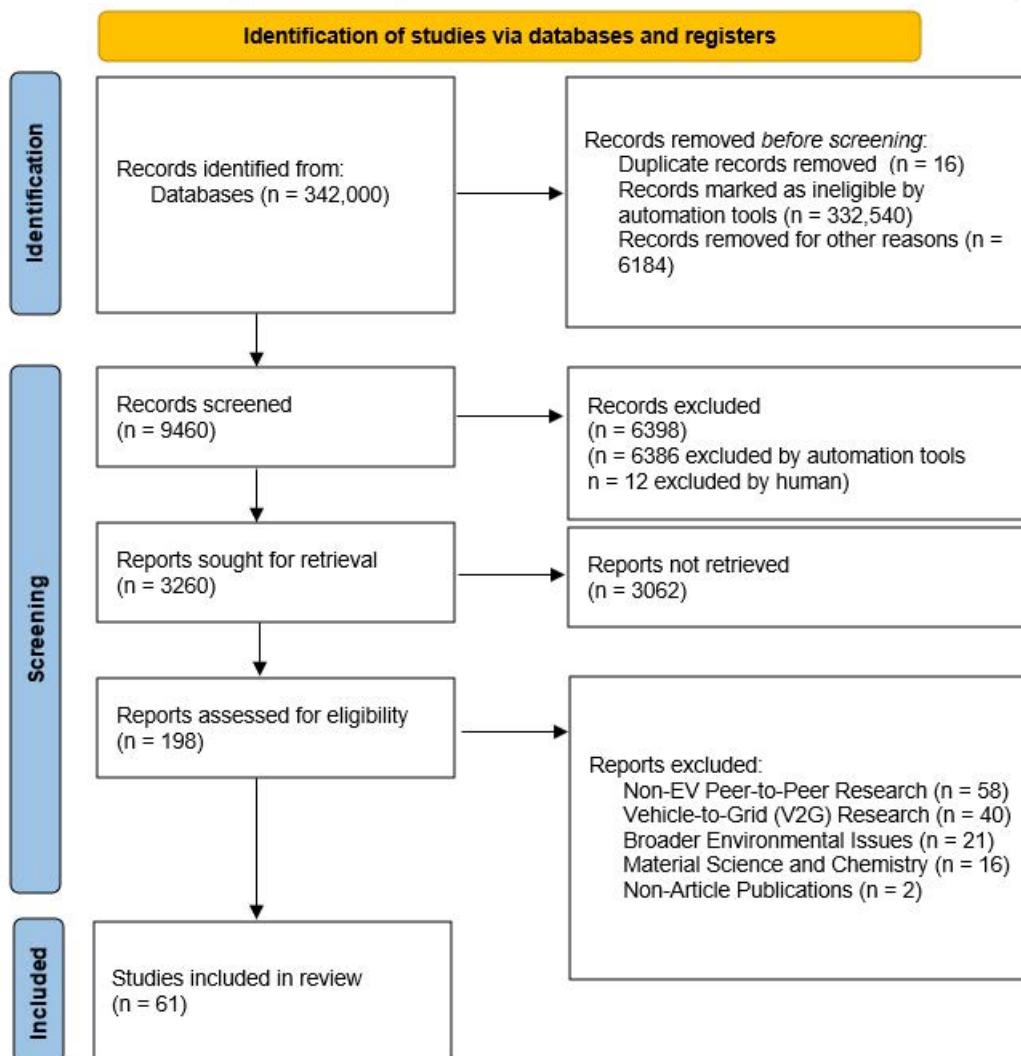


Figure A1. PRISMA 2020 Flow diagram for the systematic review [125].

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